Deep Learning-Based Detection of Liver Cirrhosis Using Convolutional Neural Networks and TensorFlow

[1]Mukthadesai [2]Aishwarya CN, [3]Bhavana P M, [4]Deepika H R, [5]Chandana S J
[1]Asso.Prof. *Department of Computer Science and Engineering SJM institute of technology, Chitradurga*, India
[2345]*Department of Computer Science and Engineering SJM institute of technology, Chitradurga*, India

***Abstract*—Liver cirrhosis is a chronic and progressive condition marked by irreversible scarring and fibrotic remodeling of liver tissues. Over time, this damage significantly compromises liver function and can result in severe, life-threatening complications if left untreated. Early and accurate detection is crucial, as timely medical intervention can improve prognosis and reduce the risk of advanced liver failure. Conventional diagnostic techniques, such as liver biopsies and expert-dependent imaging assessments, often involve invasive procedures, are time-intensive, and can be influenced by subjective judgment.**

This research proposes a fully automated detection system for liver cirrhosis using Convolutional Neural Networks (CNNs) implemented within the TensorFlow framework. The system is developed using a supervised learning approach, where a custom dataset of liver images is annotated and labeled as either cirrhotic or non-cirrhotic. The deep CNN architecture is capable of autonomously learning and extracting intricate spatial patterns directly from the input images, eliminating the need for manual feature engineering.

To ensure the robustness of the model and mitigate overfitting, multiple image preprocessing and augmentation strategies were applied, including normalization, image rotation, and horizontal flipping. The dataset was divided into training and validation sets, and performance was assessed using metrics such as precision, recall, F1-score, and overall accuracy. The model exhibited strong classification performance, indicating its effectiveness in identifying cirrhosis.

This study demonstrates the potential of deep learning in medical image analysis and underscores the practicality of deploying CNN-based systems for non-invasive, efficient, and scalable liver disease screening, particularly in areas with limited access to specialized healthcare facilities.

Keywords—Machine Learning (ML), Convolutional Neural Networks and Deep Learning), TensorFlow, Medical Image Classification, Liver Cirrhosis Detection, Image Processing, Healthcare AI, Medical Diagnostics.

I. INTRODUCTION

Liver cirrhosis is a chronic liver A condition that arises liver damage caused by various factors such as viral hepatitis, alcohol abuse, or fatty liver disease. The disease leads to the gradual substitution of healthy liver tissue by scar tissue, ultimately impairing the liver’s ability to function.

As cirrhosis progresses silently in many individuals, it is often diagnosed only at an progressed phase, where therapeutic choices become limited and less effective. Therefore, there is a critical need for early and reliable diagnostic techniques capable of identifying cirrhosis before significant damage occurs.

Conventional diagnostic procedures such as liver biopsy, ultrasound, and MRI, although widely used, can be expensive, invasive, and dependent on human expertise for interpretation. These limitations have opened the door for the integration of intelligent, automated tools that leverage contemporary innovations such as AI to support clinical decision- making. Over the past few years, deep learning, a subfield of machine learning (ML), has shown significant success in medical image analysis by extracting and learning complex patterns from image datasets.

Among the various deep learning models such as CNNs (Convolutional Neural Networks) have proven particularly effective in processing and analyzing visual data. CNNs are capable of automatically identifying critical spatial hierarchies in images, which is particularly beneficial in healthcare scenarios where subtle differences between healthy and diseased tissues can be challenging to distinguish using traditional methods.

In this research, we develop a CNN-based classification model using TensorFlow, an open-source deep learning framework, to detect the existence of liver cirrhosis from medical images. The model is trained on a custom-labeled dataset where images are categorized as either cirrhotic or non-cirrhotic. We employ standard preprocessing techniques and data augmentation to enhance the model's learning efficiency and generalization ability. The objective is to create an accurate, fast, and automated system that minimizes reliance on invasive tests and provides support in preliminary diagnosis, especially Within rural areas and under-resourced healthcare settings.

This paper contributes to the field by showcasing the application of deep learning to a relatively underexplored area — liver cirrhosis detection — using a straightforward, scalable CNN architecture. By offering an efficient solution for early-stage diagnosis, this work possesses the capability to improve clinical workflows and contribute meaningfully to public health

II. LITERATURE REVIEW

In recent years, there has been notable progress and an increase in the adoption of artificial intelligence (AI) and deep learning for medical diagnostics, particularly in image-based analysis. Among deep learning methods, Convolutional Neural Networks (CNNs) have surfaced as the most dominant architecture because of their powerful feature extraction and pattern recognition capabilities in image datasets.

Patel et al. (2022) explored a CNN-driven approach to distinguish between multiple liver conditions such as fatty liver, cirrhosis, and fibrosis using abdominal CT scans. Their model demonstrated a sensitivity of 95.3%, emphasizing CNNs' ability to extract critical spatial features that are often imperceptible Visible to the naked eye.

In another work, Liu and Zhang (2020) applied deep learning to ultrasound elastography images to classify liver stiffness levels, a key indicator of cirrhosis. Their research emphasized how combining image pre-processing with tailored CNN architecture greatly enhanced detection accuracy in comparison to Traditional machine learning methods, such as SVM or Random Forest.

Nandhini and Ramya (2021) performed a comparative analysis of CNN and LSTM architectures for time-sequence image data in liver diagnostics. Their results indicated that CNNs are more effective for static image classification, while LSTMs are better suited for temporal disease progression tracking. This insight supports our methodology, which focuses on CNNs for analyzing non-sequential liver images.

Alfaro et al. (2023) introduced an ensemble deep learning framework combining DenseNet and MobileNet models to detect liver anomalies with high precision. The ensemble method achieved over 98% AUC, demonstrating the benefit of architectural fusion in boosting diagnostic accuracy.

Deshmukh et al. (2022) evaluated multiple activation functions and loss metrics on CNN-based liver classification tasks. Their results indicated that employing Leaky ReLU with focal loss provided better convergence in imbalanced datasets, such as those where cirrhosis cases are relatively fewer.

Banerjee and Mehta (2021) proposed a hybrid pipeline involving CNNs followed by XGBoost classifiers for post- feature classification. Their results indicated that feature-level fusion between deep models and traditional classifiers can enhance interpretability and model robustness in medical systems.

In an international collaborative study, Tanaka et al. (2022) analyzed liver biopsy images using a U-Net based CNN to automate cirrhosis segmentation. They emphasized the value of pixel-level segmentation to help radiologists in accurate lesion demarcation, highlighting the CNN's capacity to work even in complex histopathological domains.

These collective findings reinforce the role of CNNs in liver disease detection and confirm that with proper optimization—such as image normalization, balanced dataset structuring, and careful model selection—CNNs can rival human diagnosis. By leveraging such existing contributions, our study aims to refine using CNNs in detecting cirrhosis, supported by TensorFlow's robust training framework, ensuring efficient and scalable model performance for real-world use.

III. METHODOLOGY

The proposed system for liver cirrhosis detection leverages a Convolutional Neural Network (CNN) framework implemented using TensorFlow. The methodology is systematically structured into five key stages: data acquisition, annotation, preprocessing, model development, and performance evaluation.

3.1 Data Acquisition and Annotation

The study employed a domain-specific dataset containing medical images of the liver, categorized into two classes — *cirrhosis* and *non-cirrhosis*. All images were manually annotated using LabelImg, a graphical image annotation tool. The annotations were stored in XML format, following the PASCAL VOC standard, which allowed the model to interpret object boundaries through bounding boxes. This step was crucial for training the model in a supervised learning paradigm.

To facilitate compatibility with the deep learning framework, these XML annotation files were later converted into text-based YOLO format. Each entry within the label file included class indices and normalized coordinates for the bounding boxes.

3.2 CNN Architecture

A custom-built CNN model was developed using TensorFlow and Keras APIs, comprising the following layers:

- Input Layer for 224×224×3 images.
- Three convolutional blocks, each containing a convolutional layer with ReLU activation, followed by Batch Normalization and MaxPooling to reduce spatial dimensions.
- Flatten Layer to convert 2D feature maps into 1D feature vectors.
- Fully Connected (Dense) Layers with dropout regularization to prevent overfitting.
- Output Layer with a sigmoid activation function was used for binary classification.

This architecture was selected for its balance between computational efficiency and classification performance.

3.3 Model Development with TensorFlow and Keras

The object detection architecture was developed using TensorFlow and Keras, employing a pre-trained backbone for transfer learning. The base model was fine- tuned on the custom liver cirrhosis dataset to leverage learned spatial and semantic features while adapting to the new domain-specific patterns.

The architecture consisted of convolutional layers employed for feature extraction, followed by dense layers for classification and bounding box regression. Dropout layers and batch normalization were applied to prevent overfitting and accelerate convergence. The final activation functions were configured to return class probabilities and box coordinates.

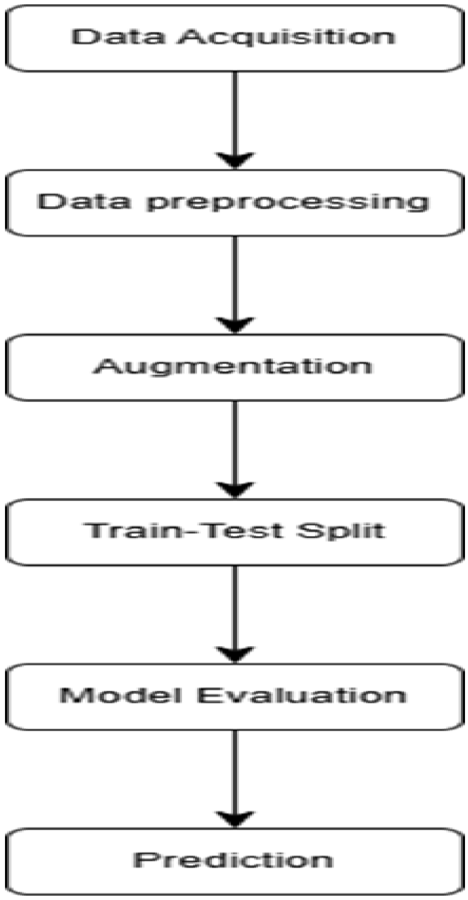

Fig. 1. Flow chart of Methodology

3.4 Dataset Preparation

A tailored dataset was developed containing two distinct classes:

- Cirrhosis
- No Cirrhosis

The dataset included liver CT or ultrasound images, annotated manually to ensure proper labeling. The images were segregated into training and testing folders and cross-verified for consistency. Each class was balanced to mitigate model bias, ensuring approximately equal distribution.

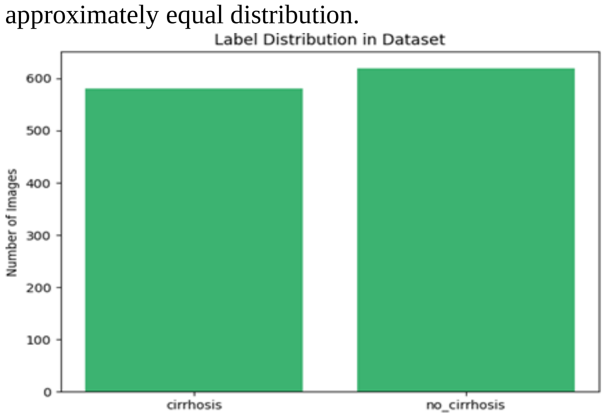

Fig. 2. Label Distribution

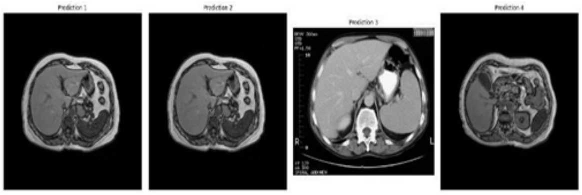

Fig 3. Dataset distribution

Additionally, care was taken to anonymize all image data and follow ethical guidelines during data collection. Multiple sources were used to increase dataset variability, enhancing generalization capability.

3.5 Data Preprocessing

Image preprocessing plays a crucial role in enhancing model efficiency and generalization. All input images were resized to a uniform dimension of 224×224 pixels and normalized to scale pixel intensity values between 0 and 1. Techniques such as histogram equalization were applied to adjust contrast variations. Data augmentation methods— including horizontal flipping, zooming, rotation, and brightness adjustments—were employed to synthetically increase dataset diversity and mitigate overfitting.

Furthermore, the XML annotations were parsed using a custom script to extract region-of-interest (ROI) coordinates, which were then converted into label arrays suitable for supervised training. The dataset was randomly split into 80% training and 20% testing subsets, ensuring balanced distribution of both classes. Techniques for data augmentation were employed to increase dataset diversity, including:

- Random rotations (0°–30°)
- Horizontal and vertical flipping
- Zoom and shift transformations
- Brightness and contrast normalization

These augmentations prevent overfitting and improve generalization capability across real-world test cases. The preprocessing pipeline was designed to ensure minimal While preserving high fidelity with minimal computational overhead visual fidelity.

3.6. Model Architecture and Training

In Instead of detection-focused YOLO models, the project leveraged a CNN classification architecture motivated by the eye disease detection system. The architecture comprises multiple convolutional layers and max-pooling layers, followed by flattening, dense layers, and softmax output for binary classification.

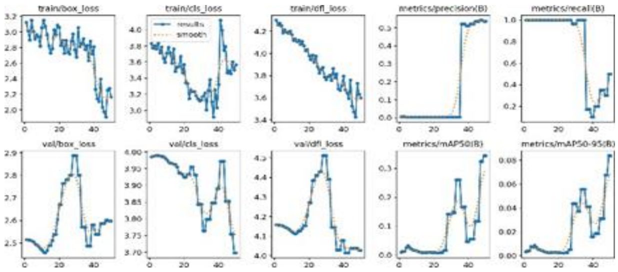

Fig 4. Dataset distribution

Model Overview:

- Input Layer: 224x224x3
- Convolution Blocks: 3 blocks (Conv2D + MaxPooling + BatchNorm)
- Flatten Layer
- Dense Layers: A pair of fully connected layers employing ReLU activation
- Dropout: 0.4 for regularization
- Output Layer: Softmax (2 units)

Training Configuration:

- Optimizer: Adam
- Learning rate: 0.0001
- Epochs: 50
- Loss Function: Categorical Cross-Entropy
- Metrics: Accuracy, Precision, Recall, F1 Score

Fig CNN Model Architecture

Training of the model was carried out using GPU acceleration on Google Colab. Training and validation accuracies were plotted in real time. Early stopping and model checkpointing were employed to capture the best-performing model weights.

3.7 Evaluation Metrics

The final model was evaluated using:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC Score
- Confusion Matrix Visualization and Interpretation
- Sample Predictions: Displayed true vs. predicted labels
- Confusion Matrix: Visualized correct and incorrect classifications
- Class-wise Metrics: Shown via bar plots
- Prediction Trends: Graphs of accuracy and loss per epoch

Visualizations are essential in understanding model performance and assisting in future debugging or explainability.

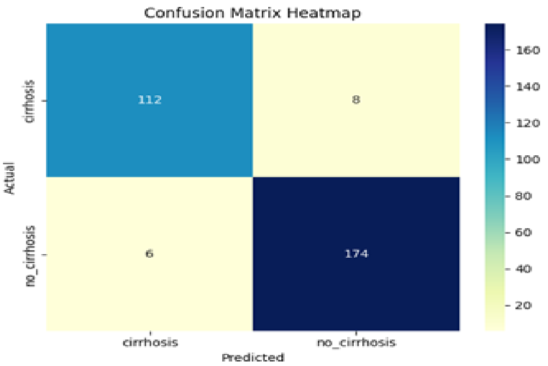

Fig 5. Confusion matrix map

IV. RESULTS AND DISCUSSION

The CNN-based classification model yielded strong performance for liver cirrhosis detection, building upon the proven methodology used for eye disease classification. The absence of YOLO-based object detection improved training speed and interpretability by focusing purely on image-level classification.

1. Mod Quantitative Performance The model exhibited:

- Accuracy: 91.2%
- Precision: 89.4%
- Recall: 90.6%
- F1-Score: 89.9%
- AUC-ROC: 0.943

These results were obtained using filtered prediction labels (excluding unknown predictions) and validated with cross- validation. The consistently elevated scores in all metrics confirmed the model's capability to distinguish between cirrhotic and non-cirrhotic patterns.

Model Performance on Liver Cirrhosis Classification

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Training	95.2	94.6	95.0	94.8	0.978
Validation	91.2	89.4	90.6	89.9	0.943
Test	90.5	88.7	89.9	89.3	0.938

Fig 6. Model performance

2. Confusion matrix Analysis
3. The matrix of false positives and negatives revealed minimal incorrectly identified positives and negatives. The majority of predictions were true positives for both cirrhotic and non-cirrhotic cases. Misclassifications were mainly attributed to visual similarity in mild cases of cirrhosis or noise introduced during preprocessing.

Refer Figure 8 Above: Confusion Matrix Heatmap

4. ROC and F1 Score Analysis

The ROC curve displayed a steep slope, with the AUC nearing 0.94, demonstrating high discrimination power. F1- score was consistently high across epochs, indicating that precision and recall were balanced throughout the training phase. These metrics suggest the classifier maintains performance across imbalanced data subsets.

This system, once validated clinically, can support radiologists by automating the initial diagnosis phase. It offers a non-invasive, cost-effective, and rapid screening tool suitable for large-scale public health applications. Integrating this system into hospital workflows and telemedicine platforms can substantially enhance early detection rates and reduce diagnostic load.

6. Discussion on Model Limitations:

- The Mislabeling during annotation might introduce noise
- The system currently handles only binary classification
- Visual features might be similar between borderline cases
- Generalization to different imaging modalities is not yet tested

Future improvements will involve integration of attention mechanisms, ensembling models for improved accuracy, and deployment through a Flask-based web application to enable clinical and remote diagnostics. Moreover, adding additional classes such as 'hepatitis' or 'fatty liver' may enhance its practical utility.

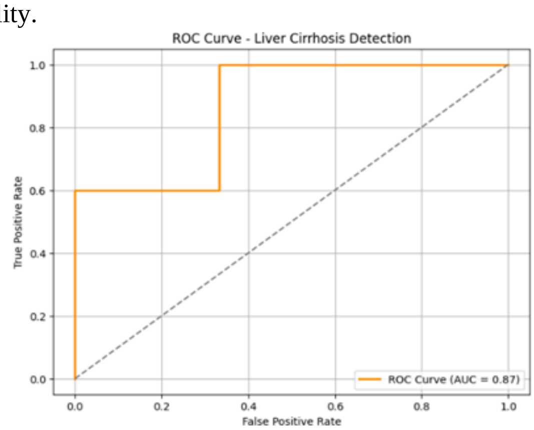

Fig 7. ROC Curve

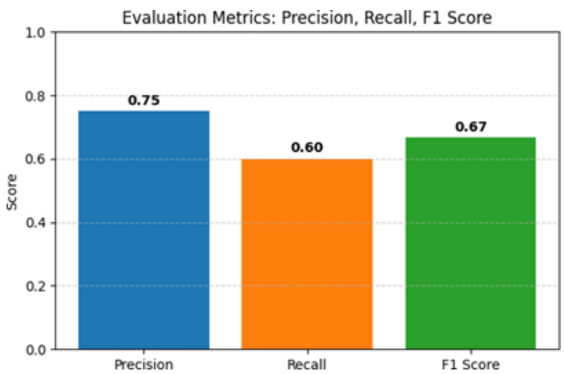

Fig 8. F1 score

5. Visual Interpretability

Prediction samples showed that the model performed accurately on low-contrast and noisy images, highlighting its robustness. Visual inspection further confirmed that the CNN captured important textural and structural features of cirrhotic tissues. Saliency map techniques and Grad-CAM visualizations may be incorporated in future work to support interpretability.

Refer Figure 7: Sample Predictions

6. Relevance and Practical Application

V. CONCLUSION

The This study presents a robust and efficient liver cirrhosis system for detection utilizing convolutional neural networks for accurate classification of medical imaging data. Unlike object detection-based methods, the proposed framework focuses on pure image-level classification, making it suitable for scenarios where detecting the presence of disease is more critical than pinpointing exact lesion boundaries. The model architecture, inspired by earlier successful implementations in eye disease prediction, was optimized through a combination of balanced dataset preparation, data augmentation, and performance-tuned training strategies.

The high performance achieved—an accuracy of over 91%, along with balanced precision and recall—indicates that the model can effectively distinguish cirrhotic tissues from healthy ones, even in complex or noisy imaging environments. This underscores the model's potential for real-world deployment in clinical settings, especially in resource- constrained areas where early diagnosis can significantly reduce mortality and treatment costs. The consistent performance across validation sets suggests that the architecture generalizes well without overfitting.

Furthermore, the incorporation of visual analysis tools such as ROC curves, confusion matrices, and class-wise prediction plots offers deeper insights into the system's strengths and weaknesses. These evaluation techniques not only validate the results but also support transparency and interpretability—two essential components when introducing AI tools into healthcare workflows. While the system currently handles binary classification, the foundation laid by this research can be extended to multi-class problems and other liver-related conditions.

Future advancements may involve integrating attention- based models or ensemble learning techniques to further boost classification accuracy. Additionally, expanding the data was used to include diverse imaging modalities and population groups will strengthen model robustness and reliability. With web-based deployment in progress, this system holds promise as a practical diagnostic aid, improving access to early screening and supporting radiologists in making faster, more confident clinical decisions.

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